Towards Guideline Compliant Clinical Decision Support System Integration in Smart and Mobile Environments: Formalizing and Using Clinical Guidelines For Diagnosing Sleep Apnea*

Patrice C. Roy, Newres Al Haider, William Van Woensel
Ahmad Marwan Ahmad and **Syed SR Abidi**
NICHE Research Group, Faculty of Computer Science
Dalhousie University, Halifax, Canada

Abstract

Assistive technologies in smart environments were developed in order to maintain and improve the quality of life of people with dementia or other health problems. In order to provide adequate support at the opportune moment, it is necessary to deploy ambient services, such as activity recognition and assistance planning. Clinical Decision Support Systems (CDSS) that implement clinical guidelines, allow for the right clinical decisions, such as diagnoses and treatment choices, to be made automatically based on patient data and other health information. While data derived from smart home services can be used in these CDSS, smart homes can be used to provide services related to clinical decisions. Mobile devices can be used in conjunction with the smart home services and a remote CDSS for sending notifications or retrieve data from wearable or built-in sensors. However, in a context where smart homes interacts with a remote CDSS, we must take into account mobility (e.g. outdoors, work), failure tolerance (e.g. connection issues with remote CDSS) and privacy concerns in order to provide minimum quality of service. Thus, CDSS must be locally deployed as a smart home service and on a mobile device. In this paper we investigate a scenario where due to the above mentioned reasons a clinical guideline compliant CDSS needs to be deployed on a mobile device and as a smart home service, where clinical data can come from either the patient (manual input) or the smart home and mobile sensors. In particular we focus on implementing and evaluating a guideline for the diagnosis of sleep apnea. Sleep apnea diagnosis is a well-suited task for this purpose as attributes for the execution of the guideline could be collected both from the patient and sensor data inside or outside the smart home environment. In order to illustrate the feasibility of CDSS as smart home service and on mobile device, the Sleep Apnea CDSS is validated on an Android smartphone and show promising results.

1 Introduction

In smart homes with ambient and wearable sensors, various services are able to provide assistance to patients diagnosed with dementia or other health problems, while maintaining and improving the quality of life(Cook, Augusto, and Jakkula 2009). Clinical Decision Support Systems (CDSS) are used to derive clinical conclusions from patient data, in order to automate and help the process of diagnosing and treating the patient (Musen, Middleton, and Greenes 2014). One way that a CDSS can be implemented is to formalize a clinical guideline (Fleetham et al. 2006), which is a document detailing best practices for diagnosing and treating patients, and use it on a knowledge base containing the patient's data. An interesting perspective is to use CDSS in a smart home setting, where data for the remote CDSS can be obtained from smart home services and mobile devices using ambient and wearable sensors. However, in order to maintain minimum quality of service for CDSS decision support, the CDSS decision process must be deployed locally as a smart home service an on mobile devices. Thus, it allows taking into account aspects concerning mobility (e.g. the patient going outside, being at work), failure tolerance (e.g. connection issues with remote CDSS) and privacy concerns. For instance, if we have connection issues with the remote CDSS, the smart home and the mobile device are able to provide services related to clinical decisions. When the patient is doing some activities outside the smart home environment or is at work, the mobile device can use built-in and wearable sensors to provide CDSS support. Finally, due to privacy issues, some clinical data are not sent to the remote CDSS or smart home services, but we are able to use smart home or mobile CDSS to infer clinically relevant conclusions and present them directly to the patient.

An ideal example domain for this integration scenario is the diagnosis of sleep apnea, which is investigated in this paper. Sleep Apnea affects at least 1 in 20 adults and its diagnosis is currently often done using an expensive sleep study that needs to be done in a hospital setting (Blackman et al. 2010). While there exist some works on detecting sleep apnea related events in smart home environments (Liu et al. 2014), both patient data, most likely collected through a mobile device, as well as facts derived from sensor data are needed in order for the current clinical guidelines on this health condition to be implemented. According the official Canadian guidelines for Sleep Apnea, there are a number of attributes required in order to reach a diagnosis, many that could be best be captured during the day, when the patient could easily be outside the smart home environment (such as impaired concentration or daytime fatigue). Furthermore, even in the cases where the patient is at home,

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certain data points, such as having an unrefreshing sleep can easily be captured immediately by manual user input on a mobile device that could be lying next to the bed, which is often used as an alarm clock. While the proposed possible integration of various sources of data (patient input, mobile sensors, home sensors) can have a lot of potential, an important aspect to investigate whether the current guideline, with the various data points derived from it, can be implemented in a CDSS and run on a mobile device or as a smart home service. Investigating the feasibility of such systems is the main goal of this paper. Thus, a mobile version of the Sleep Apnea CDSS decision process is validated on an Android smartphone. Furthermore we also intend to describe, based on this implementation, what research and implementation tasks are needed, in order to arrive at the a fully functional, and generic framework, that can seamlessly take into account the CDSS, smart homes and mobile devices aspects.

This paper is organized as follows: Section 2 presents an overview of Clinical Decision Support Systems, with additional description of possible issues and tasks in the fields of CDSS in smart (home) and mobile environments. Afterwards, Section 3 illustrates a CDSS within these two fields by presenting the decision process for a Sleep Apnea CDSS. In Section 4, we present a validation of the Sleep Apnea CDSS decision process on a smartphone. Finally, we present conclusions and future works in Section 5.

2 Clinical Decision Support Systems

Clinical Decision Support Systems (CDSS) (Musen, Middleton, and Greenes 2014) are systems that provide patients, clinicians, medical staff or other individuals with relevant knowledge to improve the patient's health and clinical outcome. These systems have several capabilities: 1) use information from the current clinical context to retrieve pertinent information, 2) provide patient-specific and contextual alerts, reminders, clinical order sets, diagnoses or other recommendations for direct actions, 3) organize information in order to facilitate decision-making and action. In order to provide the right decision-making process, patient data must be acquired and validated. There are several ways for data acquisition: keyboard entry, speech input, scanning forms, real-time data monitoring, and intermediaries who transcribe written or dictated data. In order to comply with the state of the art, and to provide interoperability, CDSS often follow specifics medical terminologies related, for instance, to diagnostic evaluations (SNOMED Clinical Terms[1]) and clinical procedures (LOINC[2]).

Concerning the decision-making process of CDSS, there are a wide range of approaches: 1) information retrieval depending on contextual information from, for instance, an electronic heath record (EHR), 2) encode problem-specific flowcharts, such as clinical protocols and guidelines, 3) probabilistic reasoning using, for instance, Bayesian models, 4) machine learning techniques such as, linear regression, support vector machine and artificial neural networks, 5) rule-based approaches where, for instance, rules related to a guideline-based therapy are represented as Medical Logic Modules (MLM) by using the Arden syntax from the HL7 standard[3], and 6) ontology-driven CDSS where Semantic Web tools such as RDF (Resource Description Framework), OWL (Web Ontology Language) and RIF (Rule Interchange Format)[4] are used.

There are a wide variety of different diseases, domains and use cases that CDSS have targeted. The scenario that we target in this case concerns CDSS integration in both Smart Environments and Mobile Settings, for which we give a brief overview.

2.1 CDSS Integration in Smart Environments

CDSS integration in smart environments, such as smart homes(Cook, Augusto, and Jakkula 2009), has a number of benefits. While several CDSS use data acquired manually from patients and medical staff via a web or mobile application, in a smart environment the real-time monitoring provided, for instance by smart home services and smartphones, can be used. Such monitoring allows the retrieving of clinical facts in a less intrusive way, even under scenarios when the patient is unable to recognize a clinical event, or is unable to react and input the correct clinical fact immediately.

In the smart home environment, we can have deployed services that use ambient or wearable sensors in order to infer new clinical facts, which are sent to the remote CDSS. The smart home effectors (speakers, TVs, tactile screens . . .) can be used to notify the patient concerning alerts resulting from the CDSS decision process. These notifications can be optimized and personalized according, for instance, to the patient profile and CDSS user preferences. The smart home services can also use patient interactions with smart home applications in order to evaluate clinical facts that would normally be derived from standard questionnaires.

In order to infer new clinical facts from low-level sensor events, high-level recognition/monitoring algorithms must be developed and implemented. The smart home services that use these new algorithms must define policies in order to determine when to send new clinical facts, as an input knowledge for the CDSS. This is important in order to not to overwhelm the reasoning engine in the CDSS with low level data. For instance, a new clinical fact identical to previous ones could be sent to the remote CDSS only when a threshold is exceeded concerning the elapsed time since this specific clinical fact was first observed.

Finally, a local version of the CDSS decision process can be deployed as a smart home service in order to provide minimum support if we have connection problem with a remote CDSS. Formal validation methods can be used to provide minimum quality of service for CDSS (remote and local)(Guillet, Bouchard, and Bouzouane 2013). The local CDSS decision process can be a subset of the remote CDSS decision process, where decision results is restricted to urgent alerts or decisions relevant to a smart home context.

[1] http://www.ihtsdo.org/snomed-ct/

[2] http://loinc.org

[3] http://www.hl7.org

[4] http://www.w3.org/standards/semanticweb/

2.2 CDSS for Mobile Settings

CDSS in mobile setting often focus on self-diagnosis or self-management tasks. With self diagnosis, the potential patient is able to detect and diagnose a possible condition using only the mobile device and attached mobile sensors. While the accuracy of such measurements is sometimes only a fraction of that in hospital clinical settings, such self diagnosis can often be performed as an initial, inexpensive step, before more exhaustive diagnosis is performed. Self-management programs that enable patients to achieve efficacy in the management of their diseases, which in certain cases has been shown to improve patient clinical outcome (Abidi, Abidi, and Abusharek 2013).

Smartphones and tablets are often used in certain CDSS, where a patient diary application allows the patient to enter clinical facts concerning, for instance, health measurements and patient symptoms. A local version of the CDSS decision process can be deployed on such devices. This allows a minimum support if there are connection problems with the remote CDSS, when the patient goes outside the smart home, or when the patient does not want to send privacy sensitive information.

An example of a system that implements such a mobile CDSS is the Integrated Management Program Advancing Community Treatment of Atrial Fibrillation (IMPACT-AF) project which aims to provide a web and mobile-based CDSS for patients with Atrial Fibrillation (AF)(Abidi, Abidi, and Abusharek 2013). Thus, the IMPACT-AF CDSS purpose is to improve the knowledge about AF management, the healthcare processes and health outcomes for people with AF. This ontology-driven CDSS uses rules in order to send recommendation and notifications/alerts/reminders to patients and medical providers. Patients can use a mobile application in order to send medical measurements (blood pressure, hearth rate, AF symptoms ...) and receive notifications from the remote CDSS or local reasoning engine.

There are a number of intersections with the previously mentioned areas that are interesting to explore. In the example that we describe, we focus in particular of the feasibility of running a CDSS system that uses facts derived from smart and mobile environment purely on a mobile device. For this example we explain the domain of Sleep Apnea, and describe and formalize the current clinical guidelines for its diagnosis.

3 Sleep Apnea CDSS example

In order to illustrate CDSS integration in Smart Environment, we present the decision process of a Sleep Apnea CDSS, which can be deployed locally as a smart home service or on a mobile device. A validation of this decision process is presented in Section 4.

3.1 Sleep Apnea

Sleep Apnea affects at least 1 in 20 adults (Canadian Thoracic Society[5]). It has several symptoms that include recurrent awakening, loud snoring, choking episodes, non-restorative sleep and daytime sleepiness. Patients with sleep apnea are more likely to have car crashes due to excessive sleepiness and falling asleep while driving. Sleep apnea usually leads to an increased risk to develop cardiovascular and cerebrovascular disease. There are three different types of sleep apnea: 1) *Obstructive sleep apnea* (OSA), the most common type, 2) *Central sleep apnea*, and 3) *Complex sleep apnea*. In this paper we mainly focus on obstructive sleep apnea, and unless specified explicitly otherwise, by the term sleep apnea we refer to OSA. Usually, an individual with sleep apnea is not aware of having difficulty breathing, and is often recognized by others witnessing the individual during sleep apnea episode or is suspected because of the observed symptoms. This makes it an ideal candidate for a smart home scenario, where sensors could detect such episodes automatically without the need for a human intervention, or recognitions of said symptoms..

The diagnosis of sleep apnea normally happens through a sleep study/testing process.There are four levels of evaluations for sleep testing (Blackman et al. 2010):

- Level 1: Complete laboratory polysomnography (PSG).
- Level 2: Full ambulatory polysomnography.
- Level 3: Portable monitoring with three or four channels, including hearth rate and pulse oximetry.
- Level 4: Portable monitoring with only one or two channels, including pulse oximetry.

The polysomnography (PSG) monitors several body functions, including brain (EEG), eye movements (EOG), skeletal muscle activation (EMG), hearth rhythm (ECG), nasal and oral airflow, and pulse oximetry during sleep. As noted, while the first levels often need a full ambulatory or laboratory settings, certain monitoring could be performed in a smart (home) environment. As mentioned earlier, the full diagnosis according to the guidelines for sleep apnea is not only dependant on sensor data, but on questions and observations for which manual input is most likely needed, often in a mobile setting. To explain these attributes in detail first we need to take a look at the full decision process according to the sleep apnea diagnosis guideline (Fleetham et al. 2006), and how this is actually formalised.

3.2 Decision Process

The sleep apnea CDSS decision process uses Semantic Web tools and rule-based reasoning, in order to formalize the current Canadian guideline (Fleetham et al. 2006) for the recognition of sleep apnea. The CDSS knowledge representation uses Resource Description Framework (RDF), where facts are in the form of subject, predicate, object (s, p, o) triples. The Web Ontology Language (OWL), which has formal grounding in Description Logics (DL), allows defining restrictions on RDF datasets according to the underlying domain (e.g. healthcare). Given the ontology terminology, reasoning engines are able to make useful inference on RDF data. However, in many domains, such as clinical domain, more extensive and custom reasoning is generally required to operationalize all relevant knowledge (Berner and La Lande 2007). In the sleep apnea CDSS decision process, the reasoning process is based on rules. The rules are based

[5]http://www.lung.ca/cts-sct

on the Canadian guidelines for the diagnosis of sleep apnea (Fleetham et al. 2006).

A patient dataset comprises health factors related to sleep apnea, including clinically relevant personal information (e.g. age, gender), clinical measures and observations, and symptoms specific to sleep apnea. In this particular example we focus strictly on data points needed to run the formalized guidelines. These measures and observations can be dynamically collected from several sources: mobile patient diary (manual input), web-based CDSS (manual input), smart home services (automatic input) and smartphone monitoring services (automatic input). Concerning the automatic input, smart home and smartphone services uses high-level recognition/monitoring algorithms in order to infer clinical information from low-level sensor events (smart home sensors, wearable sensors, smartphone built-in sensors). Collectively, these data items are referred to as clinical facts. For every collected fact, the timestamp and value are recorded.

The sleep apnea ruleset is derived from guidelines for diagnosis of sleep apnea, given by the Canadian Thoracic Society. A total of 9 rules were derived for the Obstructive sleep apnea (OSA):

Rule 1: If we observe excessive daytime sleepiness that is not better explained by other factors, then the individual satisfies diagnostic criteria A.

- The individual can use the Epworth Sleepiness Scale(Johns 1991) (questionnaire or mobile application) to evaluate daytime sleepiness.

Rules 2–6: If we observe condition X, then the individual has a symptom related to diagnostic B.

- condition X is taken from the following:

1. choking or gasping during sleep
2. recurrent awakening from sleep
3. unrefreshing sleep
4. daytime fatigue
5. impaired concentration

Rule 7: If we observe five or more obstructive apnea events per hour during sleep, then the individual satisfies diagnostic criteria C.

- An event is characterized by complete cessation of, or transient reduction in, breathing with maintained or increasing respiratory effort. The event last 10 seconds or longer and we must observe a clear decrease from baseline with or without oxygen desaturation (4% or greater).

Rule 8: If the individual satisfies diagnostic A and diagnostic C, then the individual is diagnosed with OSA.

Rule 9: If the individual satisfies diagnostic C and at least 2 different symptoms related to diagnostic B, then the individual is diagnosed with OSA.

3.3 Integration

As mentioned in Section 2, integrating Clinical Decision Support Systems (CDSS) with smart home services and mobile devices have many advantages.

As it can be viewed from the clinical facts used within the rules, certain facts can be derived through sensors, such as counting obstructive sleep apnea events, and measuring symptoms that occur during sleep. For others, such as daytime fatigue and impaired concentration manual input can be needed, and often within a mobile context, as these symptoms can occur any time during the day, even outside the smart home environment.

For facts entered by the patient, a mobile application can be used to capture these datapoints at all possible times. The use of portable monitoring device for the diagnosis of sleep apnea is useful for the management of patients with uncomplicated sleep apnea(Blackman et al. 2010), which can be used for capturing sleep apnea events that require sensors even in a smart home setting..

Sensors on mobile devices can be applied as well for automated detection. For instance, the smartphone's built-in sensors can be used to detect symptoms from sleep apnea. The smartphone can send breathing (built-in microphone) and movement (accelerometer) patterns and location (cell tower triangulation) to an external server, which evaluate if the patient has sleep apnea (Alqassim et al. 2012).

Clinical facts can also be inferred from wearable sensor events while sleeping (Cheliout-Heraut et al. 2011), and could be integrated within the smart home environment. Smart home service or smartphone monitoring services can retrieve data from wearable sensors and use it to infer new clinical facts. For instance, ElectroCardioGram (ECG) data from a wearable sensor is processed in real-time by a mobile device in order to determine if the patient has apnea (Sannino, Falco, and Pietro 2014). In another approach, a wrist accelerometer sensor can be used in order to determine sleep activity pattern and aberrant changes in the normal sleep/wake cycles (Biswas et al. 2009).

The smart home sensors can be used to retrieve clinical facts related, for instance to sleep awaking. For instance, the smart home can retrieve data from a dense pressure sensitive bed sheet in order to recognize the sleep posture (Liu et al. 2014). In addition, the smart home can use data from a near-infrared video in order to infer the quality of sleep according to motion information (Liao and Yang 2008).

Finally, we can use mobile application or smart home service in order to evaluate clinical facts based on questionnaire. For instance, the Epworth Sleepiness Scale concerning the daytime sleepiness can be evaluated by filling a questionnaire in the mobile application or on a smart home screen, or by using observed dozing events.

4 Sleep Apnea CDSS validation

To validate the decision process of a CDSS integrated with smart homes, we implemented the Sleep Apnea CDSS decision process on an Android smartphone. The purpose of this validation is to test the feasibility of using the decision process on a smartphone, where data may be obtained from the patient diary application, the smart home services or local smartphone monitoring services. For this validation, we assume that we have received data from at least one of these sources, and we focus on the evaluation the reasoning process on this data.

4.1 Reasoning engine

The implementation of the decision process on the Android smartphone use AndroJena, an Android version of the Apache Jena framework. Apache Jena[6] is a well-known Java framework for working with Semantic Web data. Regarding reasoning, AndroJena supplies an RDFS, OWL and general-purpose reasoner. The general-purpose reasoner provides both forward and backward chaining, respectively based on the standard RETE algorithm (Forgy 1982) and a Logic Programming (LP) engine. In addition, the reasoning engine supports a hybrid execution model, where both individual rule engines are employed in conjunction.

4.2 Methodology

In our validation, we study the following performance metrics for the decision process:

- *Data and rule loading times*: Time needed to load data and rules into the reasoning engine.
- *Reasoning times*: Time needed to execute the rules on the dataset and infer new data.
- *Memory consumption*: Memory consumed by the reasoning engine.

For the decision process validation, we use a Sleep Apnea decision support ruleset encompassing a total of 9 rules. For each rule, the rule head refers to the latest clinical fact of a certain type (e.g. *recurrent awakenings from sleep*) and checks whether its matches a specific value (boolean, number). If so, a clinical conclusion is inferred in the rule body, indicating the severity of the situation, type of conclusion, label and identifier of the triggered rule.

We generated datasets (profiles) containing clinical data (measurements) described in Section 3.2, whereby fact values were created based on ranges encompassing both clinically normal situations as well as abnormal situations. In order to investigate the scalability of mobile reasoning, our benchmark consider a sequence of datasets, each containing an increasing amount of data according to the number of days of data (1 to 7 days). For each dataset configuration (days of data), we have 10 generated datasets (total of 70 datasets).

In each generated dataset, a single day of data has the following number of statements per measurements:

- 1 excessive daytime sleepiness statement,
- 5 chocking or gasping during sleep statements,
- 5 recurrent awakenings from sleep statements,
- 1 unrefreshing sleep statement,
- 5 daytime fatigue statements,
- 5 impaired concentration statements,
- 1 statement concerning the number of sleep monitoring reported apnea events.

It should be noted that the ruleset and datasets are intended as a representation of clinical facts that are translated into clinical conclusion. Issues with capturing knowledge from smart home services or mobile device and mapping onto clinical information, while being relevant for the integration, are outside the scope of this validation.

To minimize the impact of background OS processes on results, we ran each performance validation 20 times and calculated the average execution times. Memory usage is measured by using the Android API in order to obtain a heap dump, which was later analyzed using the Eclipse Memory Analyzer[7] (MAT). Finally, we note that to evaluate the decision process, we relied on the default configuration settings for AndroJena, which uses the hybrid execution model (see Section 4.1).

The benchmarks were performed on a Samsung Galaxy SIII (model number GT-I9300), with a 1.4GHz quad-core processor, 1GB RAM and 16GB persistent storage. The installed Android OS was version 4.3 (Jelly Bean) with API level 18. This model is currently two generations old at the time of writing (with the new Galaxy S5 model soon to be released). As such, this better reflects a real-world scenario, where users typically do not possess the latest device model.

4.3 Results

The validation shows promising results for using CDSS on mobile phone. The results presented in Table 1 shows, for each dataset configuration (number of days of data), the average times of the loading (data and rules) and rules execution steps and the average memory usage for the reasoning process. Each dataset configuration has 10 datasets. We note that memory measurements were taken right after the reasoning step was performed; and before any cleanup has occurred (e.g., releasing resources occupied by the engine).

# days of data	# triples	load triples	create rules	execute rules	memory usage
1	109	107	33	45	174
2	201	180	33	63	216
3	293	223	54	62	235
4	385	322	38	66	261
5	477	307	31	69	292
6	569	252	21	39	319
7	661	371	54	82	350

Table 1: Datasets loading and rules creation and execution time (ms) and memory usage (KB)

We note that the average time for loading the data and executing the rules and the average memory usage increase with the number days of data. Since we load all the dataset, the rules are executed on all triples related to clinical measures and observations. In order to optimize the reasoning process, we should only load the latest value for each clinical measure, but it could be possible that new rules, using previous values, are introduced in the decision process. Since the current rules need to use the latest value, the decision process execution time could be improved because the loaded subset of the dataset will have only triples related to latest

[6] https://jena.apache.org/

[7] https://www.eclipse.org/mat/

values, but by being able to load in multiple days worth of data, we show that the system could potentially handle larger datasets, and possibly more complicated rules, should the guidelines change to take these data into consideration. Finally, AndroJena is based on a framework that was not meant to mobile reasoning, thus it is possible that the reasoning engine is not optimized for mobile device. Nonetheless even the largest example in this case was executed according to the guidelines in reasonable amount of time and in the future better results could be expected once mobile reasoning frameworks mature.

5 Conclusion and future works

This paper focussed on the functioning of CDSS in the intersection of smart (home) environments and mobile frameworks, and it has shown that a guideline compliant CDSS system can be implemented on currently available mobile devices, in the case of sleep apnea diagnosis. While this validation was limited in scope, as we did not tackle the precise derivation of sensor data into the used clinical facts, it shows nonetheless that with such set of inferred clinical facts, interesting and clinically relevant problems can be tackled.

While the validation goals was to evaluate the feasibility of local CDSS reasoning process on a smartphone using clinical guidelines, future works are needed. Firstly, the reasoning process must be validated with dynamic data, where clinical measures and observations are obtained from manual inputs from the remote CDSS (web-based) and the patient diary mobile application and automatic inputs from the smart home services and smartphone monitoring services. In order to provide clinical measures and observation from smart home services, we must develop high-level recognition/monitoring algorithms in order to infer clinical information from low-level sensor events. Another interesting perspective concerns the handling of several diseases at the same time (single CDSS or several CDSS working together). Finally, by making available real-time clinical facts retrieved from smart home services and mobile devices, it is possible to improve clinical guidelines that are used in CDSS. For instance, smart home services used to retrieve clinical facts can be less intrusive than standard portable monitoring devices used for disease diagnostic/supervision at home, and guidelines can be based not only on single day measurements but several days worth of sensor and other input data.

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